Effects of GDP on Violent Crime

Benjamin Northrup

Jonathan Klaer

1. Introduction

There is a significant body of research on crime, and the economic factors that could be correlated to criminal activity, and the effects of crime on the economy. Unemployment, poverty, and education are widely touched upon subjects, but few studies have looked at GDP as an influencing factor in criminal activity within the United States.

The motivation behind this study arises mainly from a lack of study on the broader effects of GDP and GDP per person on crime rates. Since GDP per capita can be used as a good proxy for personal wealth, GDP per capita should have a measureable effect on violent crime rates. Most available literature focuses on more specific factors that, while each having effects on GDP are much smaller in scope. By looking at an overarching statistic, we hope to provide insight that can be used in future studies. We hypothesize that GDP per capita, being an indicator of personal wealth, will partially negatively explain crime rates, represented as H_1: GDP per capita < 0, H_0: GDP per capita = 0.

2. Literature Review

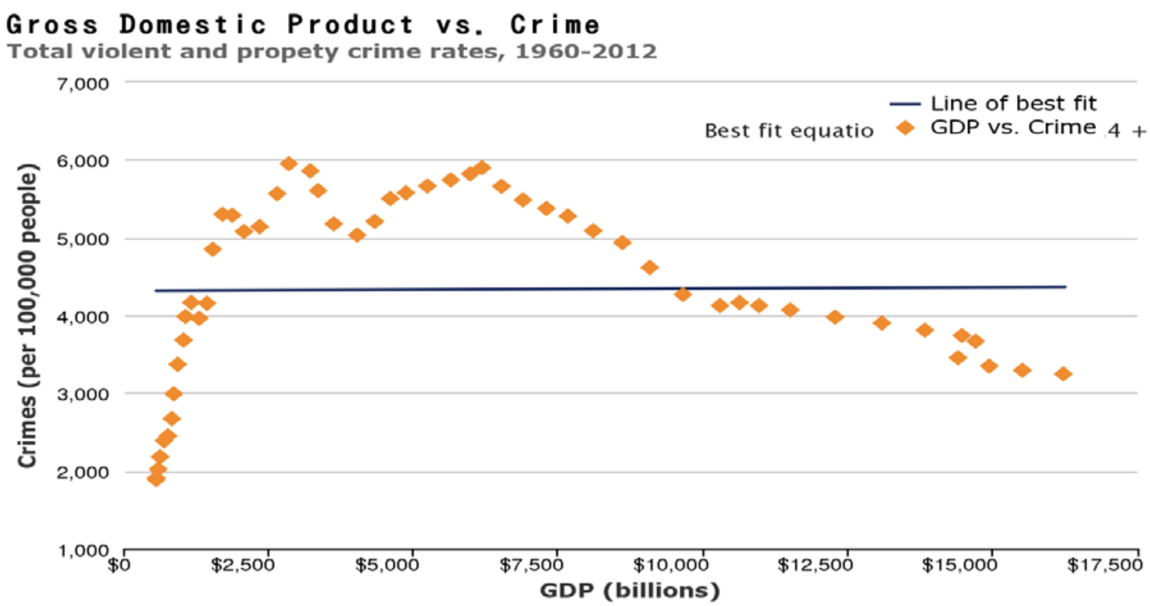
In this section, we will examine previous studies that relate to the prediction of violent crime rates. The first subsection looks at the relationship between GDP per capita and crime rates, the second subsection looks at the relationship between population density and crime rates, and the third subsection discusses how police are already using data analytics to predict crime rates.

2.1. The Relationship Between GDP per Capita and Crime

The Economist (2011) looks at the relationship between GDP per capita and crime at the state level during the recession from 2007 until 2010. At that time, crime rates had been dropping for two decades nationwide and the Economist wanted to investigate whether this trend would continue through harsh economic times. The Economist developed two main hypotheses: 1. Crime rates will increase as people get poorer and more desperate for money and 2. The victims of crime will get hit, thus reducing the opportunities for criminals to steal. By using crime rates from the US Department of Justice, the Economist was able to conclude that those states hit hardest by the recession had the biggest drop in crime rates. This conclusion backs up the second hypothesis, but the Economist was unable to justify that completely as other factors could contribute to the drop in crime.

Roman (2013) conducted research to examine the relationship between GDP and violent and property crime rates from 1960 until 2013. He begins by outlining the difficulty in testing the hypothesis that big macroeconomic factors explain crime trends. ‘Crime obviously affects macroeconomic factors as well as being affected by them’, thus causing an interdependent relationship among the two. Roman (2013) looks at the same two hypotheses as the Economist: 1. Criminologists believe that tough economic times make people more willing to commit crimes and 2. Economists believe that better economic times increase crime. By examining the relationship between GDP and crime pictured in Figure 1, Roman (2013) could not conclude a relationship between economic growth and crime.

Figure 1: Roman (2013) GDP versus Crime Scatter plot



Roman (2013) suggests that there is more to predicting crime than just economic conditions.

2.2. The Relationship Between Population Density and Crime

Christens and Speer (2005) investigate the relationship between population density and violent crime in single U.S. city, Nashville, Tennessee. They wanted to test two opposite theories. One theory suggests that population density and crime would be inversely related, while another theory suggests the opposite. Christens and Speer (2005) built models using the data from the urban center of the city compared with the entire county and the non-urban parts of the county. In conclusion, they found a non-significant negative correlation between population density and crime in the urban areas, while finding a non-significant positive correlation in the county.

2.3. Police Using Data Analytics to Predict Crimes

France-Presse (2012) discusses the shift from police brawn to police analytics in order to predict crimes around the world. A growing number of policemen are shifting towards a new kid of technology called ‘predictive policing’ in order to make crime prevention more efficient. These police are starting to use software tools with predictive analytics, based on algorithms that aim to predict crimes before they even happen. With the premise that criminals follow patterns, police are now able to effectively determine where the next crime will occur to increase their chances of preventing it. This software is comparable to that of Amazon where they use customer-purchasing trends to predict future sales. Instead, here they use past crime statistics to predict future crime. After employing this new technique in Memphis, Tennessee, officials claimed that serious crimes decreased 30 percent, while violent crimes specifically fell 15 percent. After the success found in Memphis, this new technology has spread worldwide, including London, Poland, and a number of U.S. and Canadian cities, while various other countries have come to check out this new technology for themselves.

Friend (2013) expands on this new technology that France Presse (2012) discussed in relation to his specific location, the Santa Cruz, California Police Department. After a research paper was published in 2010 regarding the ability to predict future crimes, the Santa Cruz police department set out to accomplish this feat by developing a complex algorithm. The algorithm uses a culmination of anthropological and criminological research combined with complex mathematics to estimate crime while predicting future hot spots. This new algorithm provided twice the accuracy that the Los Angeles Police Department former practices produced. Within the first six months of the employment of this technology, the department was able to make over a dozen new arrests within hot spots and burglaries declined 19 percent. As the success is rising, the algorithm is being implemented into various other police departments around the world and was named one of the 50 best inventions for 2011 by Time Magazine.

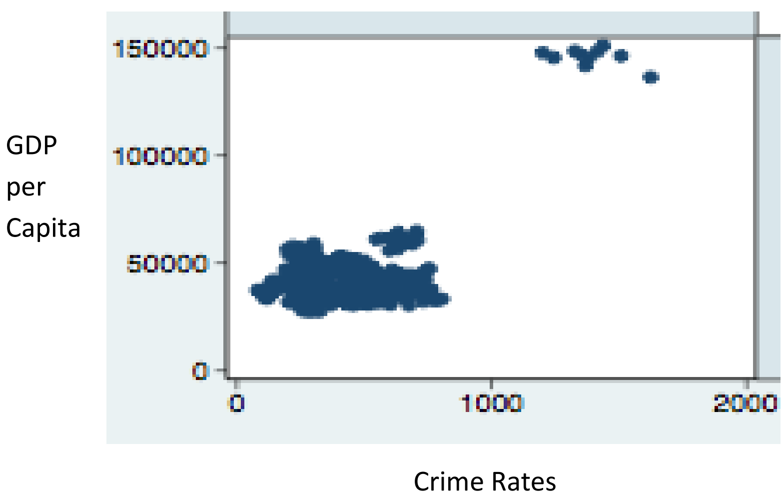
2.4. Our Addition

Our intentions for this project relate directly to the five articles written above. We intended to elaborate on the Economists’ (2011) study, studying the effect of GDP per capita on crime rates in both recession years and non-recession years. Although we will be working specifically with violent crime rates, we will touch on the hypotheses he suggested. We will be extending the work of Roman (2013) by looking at various other factors that go into predicting crime such as population density, a metric proposed by Christen and Speer (2005). In the end, we hope to add to the new algorithms that were mentioned by France-Presse (2012) and Friend (2013). We will do this by predicting violent crime rates statewide in order for the government to allocate police more effectively.

3. Data

The variables chosen for the initial, single variable regression model were GDP per capita by state, and violent crime rates by state. The state GDP per capita data was taken from the Bureau of Economic Analysis regional data, from the years 2003-2011. These GDP per capita values are in chained 2005 dollars, as to control for inflation, as the GDP per capita is used over raw GDP numbers in order to control for population variation. Violent crime rates are from the Federal Bureau of Investigation's Uniform Crime Reporting System, which takes in data on criminal activity from 18,000 different law enforcement agencies who voluntarily participate in the program. Crime statistics were divided into two separate categories: Violent crime and Property crime. Property crime is defined as burglary, larceny, theft, motor vehicle theft, arson, shoplifting, and vandalism. Violent crime is defined as murder, non-negligent manslaughter, forcible rape, and aggravated assault, and violent crime rates are defined as violent crimes committed per 10,000 people. The relationship between violent crime rates and GDP per capita is pictured in Figure 2. Notice the clustered positive relationship, with New York data point being those outliers in the extremes.

Figure 2: Crime Rates versus GDP per Capita Scatter Plot



For the multivariable regression model, several other variables were chosen, including poverty rates, high school graduation rates, unemployment rates, population density, death penalty statistics, and the total number of firearms manufactured in the state. Poverty rates, and population were taken from the United States' Census data. In order to obtain state population densities, state populations were then divided by their land area. Firearm manufacturing data was obtained from the Bureau of Alcohol, Tobacco, Firearms, and Explosives reports for the same nine-year span. Data on state death penalties was obtained from deathpenalty.org, which was used as a dummy variable, where 1 indicates a state has the death penalty, and 0 indicates a state does not.

When looking at each explanatory variable, the intuition behind each of them is obvious. High school graduation rates were chosen from the idea that, as individual education levels rise, so does gainful employment opportunities, thus lowering one's propensity to commit violent crime. Population density was used in order to see if more metropolitan areas (i.e. states with higher population densities) would affect crime levels. Poverty rates and unemployment were both considered by the same logic as graduation rates, but on an opposing side; those with less economic opportunities for advancement should be more likely to commit violent crimes. Firearm manufacturing data is slightly less intuitive, but stems from a desire to control the regression equation for states' consumption of firearms, as firearms are used heavily in criminal activity. Rationale behind the inclusion of the death penalty variable comes from the idea that, states with a death penalty may cause some people, who do not wish to receive the death penalty, not to commit violent crimes. Figure 3 sums up the data by showing the number of observations, mean, standard deviation, and the minimum and maximum data points of each variable considered.

Figure 3: Summary Statistics

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
GDP Per Capita	459	43096.8	16378.19	27605	15125
Crime Rates	459	415.1	216.28	80.2	1624.9
Graduation Rate	459	74.3	8.03	48	89.6
Unemployment Rate	459	6.6	2.24	2.04	14.5
Death Penalty	459	.69	.46	0	1
Firearms Manufactured	459	79178.5	171875.7	0	904171
Poverty Rate	459	12.99	3.35	5.4	23.1

Before results were obtained, the Gauss-Markov assumptions for linear regression were verified. The assumption of linearity of parameters holds, as can be seen in the results. Since the data used is population data, the assumption of random sampling is satisfied. As can be seen in Figure 4, the explanatory and dependent variables are not perfectly collinear, and as such, do not violate the Gauss-Markov Theorem.

Figure 4: Correlation tests

	GDP_Pe~a	Crime_~s	GradRate	Unempl~s	Pop_de~y	death_~y	firearms	Povert~e
GDP_Per_Ca~a	1.0000							
Crime_Rates	0.6144	1.0000						
GradRate	-0.1449	-0.5582	1.0000					
Unemployme~s	0.0070	0.0778	-0.1841	1.0000				
Pop_density	0.9067	0.6407	-0.1899	0.0852	1.0000			
death_pena~y	-0.2346	0.0265	-0.2407	-0.0157	-0.2535	1.0000		
firearms	0.0634	-0.0878	0.0274	0.0339	0.0058	-0.0393	1.0000	
PovertyRate	0.0097	0.4297	-0.5964	0.0629	0.1936	0.2333	-0.1814	1.0000

4. Results

The single variable regression model, multiple variable regression model, and our final restricted regression model summaries are located in Figure 5.

Figure 5: Regression Models

Dependent Variable: State Crime Rate			
Independent Variables	**Single variable Regression**	**Multivariable Regression**	**Restricted Multivariable Regression**
GDP per capita	0.008113*** (16.65)	0.0053*** (5.24)	.00739*** (6.92)
Graduation Rate		-9.85*** (-9.74)	
Unemployment Rate		-1.41 (--0.50)	
Population density		0.0312** (2.42)	0.0135 (0.98)
Firearms Manufactured		-0.000095*** (-2.61)	-0.000065* (-1.61)
Poverty Rate		9.55*** (3.61)	24.44*** (10.31)
Death Penalty		20.42* (1.40)	41.55*** (2.62)
Intercept	65.49414** (2.29)	784.76*** (6.26)	-249.74*** (-4.21)
No. of obs.	459	459	459
R-square	0.3775	0.6436	0.5663

*, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

As seen in table 1, for the single regression model of Crime Rates and GDP per capita, the coefficient obtained was statistically significant at the 1% level, and positive, meaning that for every 1000 dollar increase in GDP per capita, crime rates should grow by 8.113. This shows that in the simple model, GDP does affect crime rates, in a way that is contrary to the hypothesis.

Following this, our second model included poverty rates, firearms manufactured, GDP per capita, and graduation rates, which were all significant to the 1% level, population density, which was significant to the 5% level, the death penalty dummy variable, which was significant to the 10% level, and unemployment rates, which were determined to be statistically insignificant by itself. Having found a model with relatively good fit (an R^2 value of .6436 being an indicator), joint significance was then tested for.

As the only variable that tested to be statistically insignificant at all levels, unemployment was tested for joint significance, with high school graduation rates. This was chosen based on the correlation factors in table 2. (high school graduation rates and unemployment rates had the highest correlation, at around -.18). The third regression model listed reflects the restricted regression model, which removed graduation rates and unemployment. After using the f-statistic test, unemployment was deemed to be jointly significant with graduation rates; the f-value obtained was 48.92, which exceeds the required f-value of 10.456.

Therefore, the model that best predicts violent crime rates would be the unrestricted multivariable regression model. The model shows some very interesting phenomena, which go against the general public idea. The effects of baseline education, while thought of to be somewhat important in preventing crime, show in this model to be very significant, with a 1% increase in the high school graduation rate lowering the crime rate by 9.84. Poverty appears as a factor that nearly negates graduation rates; where a 1% increase in poverty rates increases the violent crime rate by 9.55, a 1% increase in graduation rates decrease crime rates by a little over the same factor. The coefficient for GDP per capita is rather small, but when considering the mean GDP per capita, 43096.75, this value still carries a weight in the model, though opposite to the effect hypothesized.

5. Conclusions

Several conclusions can be drawn from this study on the nature of violent crime. The main dependent variable, GDP per capita, was proven to be significant, but in a way contrary to the original hypothesis. Considering that violent crime rates, to the 1% level, are positively dependent on GDP per capita, it would seem that the growth of individual wealth would have negative impacts on society, but a less cursory look at the models presented show this to be otherwise.

The coefficient for GDP per capita is very low, less than 0.01, which makes sense, as GDP per capita has a mean value of 43096.75, and a 1 dollar increase or decrease has little bearing on an individual's decisions. When looking at the other variables, all of which are percentages except for the dummy variable of death penalty (which only takes values of 1 or 0), and their coefficients, it's easy to see that the variable dominating the total crime rate is GDP per capita. Even knowing this, GDP per capita affects certain variables, in ways that cannot be accounted for in this linear regression model.

Since poverty rates, graduation rates, and unemployment rates are controlled for in the model, GDP per capita's effects on those variable are not accounted for, nor are other positives of GDP increases. As GDP per capita increases, on average, personal wealth increases, which can only have a positive effect on poverty, and the increased GDP means higher tax inflows, allowing for higher expenditure on public services, such as crime prevention. It is possible that, as GDP per capita increases, real violent crime rates aren't increasing, but reported violent crime rates are increasing, as more law enforcement expenditure allows for more police to enforce the law.

This study provides interesting conclusions that provoke further study. Many variables that could explain some of the effects GDP per capita has on violent crime, such as expenditure on law enforcement, or firearm sales, rather than manufacture. However, because this data is very fragmented over local levels, it is very difficult to obtain. Another factor that may also explain some of the effect of GDP on violent crime is a price index for each state for each year, in order to get a more real picture of individual wealth. Over all though, this study proved fruitful, allowing for a rejection of the null hypothesis that GDP per capita has no effect on violent crime rates. Hopefully, this study will prove useful to policy makers looking forward to future criminal policy debates.

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